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Small business and economic growth: does involvement in technology make a difference? An assessment on the level of European countries.

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Abstract

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Abstract

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Introduction

Substantial agreement exists among economists and policymakers that technological innovation is a key driver of economic growth. Technological innovation implies the implementation of inventions in the production of final goods or services and as such yields productivity gains for the innovating economy. Using knowledge capital to transform existing knowledge into such inventions, the amount of research and development (R&D) efforts is an important determinant of the pace of technological innovation.

Over the past century, a large body of research has been devoted to the quest for growth models with maximal explanatory power. Neoclassical growth theorists restricted attention to the wealth enhancing effects of increased levels of labour and physical capital. In their view technological progress was an exogenous phenomenon and was to be left out of the growth equation (Solow, 1956). Both theoretically (Romer, 1986; Romer, 1990; Lucas, 1988; Aghion & Howitt, 1992) as well as empirically (Nadiri, 1993), endogenous growth scholars showed that technological innovation is an endogenous component of the process of long-term economic growth. Profit-maximising firms purposely allocate resources towards R&D and are confident they will be capable to appropriate the gains from it. Or at least a share of the gains from it: given its non-rival nature, investment in knowledge is very likely to be associated with large and persistent spill-overs to other actors. The capacity of the latter to exploit it productively forms an equally important driver of economic expansion in the endogenous growth framework (Braunerhjelm et al., 2010; Audretsch et al., 2006).

In the past decades a complementary line of research has emerged investigating the extent to which entrepreneurship can account for the part of economic growth left unexplained by the endogenous growth theorists that pulled knowledge into the equation.[1] Entrepreneurship implies the recognition of opportunities and the willingness to grasp those opportunities. (Wennekers & Thurik, 1999; Thurik & Wennekers, 2004; Stevenson & Gumpert, 1991). Entrepreneurial behaviour involves or at least can result in the introduction of new activity to the marketplace. New activity can refer to new entry and newness. Wennekers and Thurik (1999) point at these 2 major roles of entrepreneurship when relating it to economic growth. The former refers to entrepreneurs as introducing new economic activity, whether that activity is innovative or imitative. In its most formal expression, this implies the foundation of a new business. The latter perceives the entrepreneur as the innovator, transforming inventions and ideas into viable commercial activity, whether or not this implies the creation of a new firm.

[1] Schmitz (1989) pioneered this complementary branch of research by introducing entrepreneurship as a determinant of the allocation of knowledge in an endogenous growth framework.

Entrepreneurial behaviour can happen in any type of organizational structure but is often associated with small firms. Indeed, small organizations are a vehicle in which entrepreneurship tends to thrive and one can assume that the size class structure of an industry and the proportion of entrepreneurs in its working force are strongly related (Wennekers & Thurik, 1999; Carree and Thurik, 1998).

The aim of the current paper is to contribute to the abovementioned line of research associating knowledge, entrepreneurship and economic growth. More specifically we shed new light on the relationship between the prevalence of smallness in an economy and its productivity. Our research questions resulting are tested using a novel dataset covering the manufacturing industries of 23 European countries in the first decade of the new millennium. Based on a large scale mapping of patent applications to European firms, effects from knowledge-intensive small firm activity could be distinguished from effects associated with their footprint in traditional economic activity. Dynamic Panel data estimators reveal the existence of different patterns for a core of countries classified as innovation leaders and a periphery of followers.

The remainder of this paper is organized as follows. Section 2 describes and explains why the footprint of small businesses in developed economies has gradually increased in the past decades. Section 3 lists a range of theoretical motivations for associating smallness and productivity. Section 4 provides an overview of prior empirical literature explaining macro-economic performance using measures of entrepreneurship. Section 5 subsequently presents the research hypotheses and is followed by methodology, results and some concluding notes.

The shift towards smallness

Accounts of how and why economists' and policymakers' have gradually reasserted the role of small businesses in economic policy are provided in Brock and Evans (1989), Wennekers and Thurik (1999) and Thurik and Wennekers (2004). Interest for the effects of small firm activity on economic growth grew in the course of the 1970s and 1980s. The first oil crisis had set in motion a period of slow growth, inflation and high unemployment. In search for ways to overcome stagflation, the quest for alternative explanations of economic growth was reopened. In the 1960s and 1970s the perception had grown that economic progress was mainly driven by large enterprises' exploitation of all sorts of economies of scale and scope in distribution, marketing, production and R&D. The continuous growth and year-by-year increasing average firm size observed in those years were assumed to be intertwined phenomena. Small business was expected to fade away as a consequence of its own inefficiencies. Preservation of the small-enterprise sector was assumed to only serve social and political purposes (Thurik & Wennekers, 2004; Robbins et al., 2000). The upward trend in industrial activity accounted for by large firms however reversed by the late 1970s (Brock & Evans, 1989). The contribution of small firms to employment and added value in the US and Europe started augmenting year by year. It became clear that firms of different size continued to coexist in each industry. The economy achieved recovery based on economic activity relatively more underpinned by small firms; an observation that was seen as proof that smallness was not a disadvantage per se (Wennekers & Thurik, 1999).

Several scholars have provided explanations for the return towards smallness witnessed in the Western economies' manufacturing industries (Brock & Evans, 1989; Carlsson, 1992; Loveman & Sengenberger, 1991; Audretsch & Thurik, 1998). Wennekers and Thurik (1999) and Carree and Thurik (1998) list the majority of them and – to the extent they can lead to a permanent change in the size distribution of an industry – label them 'diseconomies of scale'.

A few of these factors identified in earlier research have affected the firm size distribution of industries more or less independently but the majority cannot be interpreted in isolation from the rest. In the first place, recent technological changes, such as the permanent decrease in computer costs and the lowered fixed cost of automating certain processes, have reduced the optimal firm size and the minimum scale of entry (Brock & Evans, 1989; Acs et al., 1991; Carlsson, 1992). Furthermore, declining transaction costs have lowered the need for centralization and vertical integration. In a number of cases, large firms have been replaced by new types of business communities with intermediate forms of market coordination i.e. clusters of small firms operating in geographic proximity among others of peers in the same or complementary businesses (Loveman & Sengenberger, 1991). On top of that in the 80s and 90s, together with a wave of deregulation and privatisation, one could witness the relaxation of entry barriers in some industries e.g. telecommunication, facilitating the emergence of new start-up activity (Brock & Evans, 1989; Carree & Thurik, 2002). Changes in consumer tastes induced by increasing incomes and wealth have resulted in increases in the demand for specialty products at the expense of mass-produced goods. Boutique firms have the opportunity to reign in niche industries with markets too small to exploit for large firms (Brock & Evans, 1989; Carlsson, 1992; Carree & Thurik, 2002). Next, globalisation has set in motion a wave of corporate downsizing. More foreign competition in general, together with unstable exchange rates, has led to an increase in competitive risks and a greater variability in sales. This has increased the benefits of being flexible, a characteristic that better suits the description of a small firm than of a more inert large firm seeking efficiency gains in scale (Brock & Evans, 1989; Piore & Sabel, 1984; Jackson, 1984; Acs et al., 1991). In addition, the advent in competition from emerging countries with considerably lower labour costs in the aftermath of the Cold War has forced Western manufacturers to substitute labour by equipment and technology and to shift production from high- to low-cost countries. The latter was facilitated by the communications revolution that rendered the cost of transferring information in geographic space to virtually nothing. Not coincidentally, mainly production facilities in traditional industries with standardized processes, products and organizational methods have been transferred to low-cost locations (Audretsch & Thurik, 1998; Carlsson, 1992; Thurik & Wennekers, 2004). Aiginger and Tichy (1991) provide an additional explanation in attributing this downsizing tendency to the opportunistic conglomerate merger wave of the late 1960s. Lacks of synergies induced large firms to re-concentrate on core competences and divest uncomplimentary businesses (Carree & Thurik, 2002; Carlsson, 1989). At the same time, small firms have equally benefited from quantitative and qualitative changes in the available pool of labour. Robbins et al. (2000) underline the greater presence of small businesses in general in the ‘secondary labour market’ consisting of long-term unemployed, individuals at low educational levels, part-time employees, women, certain minorities, immigrants and previously self-employed. Brock & Evans (1989) refer to the positive shock in the labour supply, fuelled by increased labour force participation of women and the entry of baby-boomers into the labour market, that refrained wage growth in the course of the 80s. Relatively more labour-intensive small businesses were in a better position to profit from that evolution than more capital-intensive large firms. Furthermore, the available labour force has not only relatively grown, it has gotten more educated (Brock & Evans, 1989) and seemingly more educated in topics with employability-perspectives in businesses characterized by a lot of start-up activity e.g. ICT. Finally, with less advanced economies attracting more and more traditional industrial activity, the comparative advantage of the ‘high labour cost’, advanced economies has shifted towards knowledge-intensive activity. Hotspots of creative, idea-driven activity that have gradually emerged in advanced economies cannot just be moved to low-cost countries ‘overnight’. Neither can the knowledge stocks that fuel economic activity in such clusters be duplicated by non-local competitors.

Essential to the dynamism of these innovative clusters is the occurrence of knowledge spill-overs between members from different sectors: universities and other public institutions, large incumbent firms, start-ups... The non-rival nature of knowledge allows these actors to tap from knowledge stocks external to their organization whereas its tacit nature – implying the need for face-to-face contact to transmit it – explains the localized reach of this externality. Spill-overs between cluster members are facilitated by a shared pool of human capital and formal and less formal interfaces maintaining and expanding the clusters' social capital. The knowledge-based economies that remain as a result of this shift are bound to be characterized by a larger footprint of small firms. The inherent uncertainty surrounding activities based on new knowledge lies at the source of this 'entrepreneurialization'. Asymmetries in the valuation of some new ideas – not rarely the ones intending the disruption of existing or the creation of new businesses – induce workers to chase them outside of existing organizations. New, small firms with more straightforward incentive structures and less biased than hierarchic incumbents by information asymmetries between inventors and managers have been shown to be more suited as a platform for such ventures. As such, the agent of change role of small firms in economies competing on innovation rather than scale is the final rationale explaining the observed shift towards smallness (Audretsch & Thurik, 1998; Carlsson, 1992; Thurik & Wennekers, 2004; Wennekers & Thurik, 1999).

Smallness vs. productivity

The abovementioned research provides a number of rationales to associate the firm size distribution with economic expansion in terms of employment or output. In the current study we aim to investigate to what extent countries gain in terms of productivity from a larger footprint of small business. The link with research addressing effects on output and employment is obvious since growth in productivity, output and employment should correlate in the longer run: increasing productivity improves competitiveness, leads to higher demand for the goods and services produced which in its turn boosts demand for labour inputs (Bosma et al., 2011; Krugman, 1994). Studies relating growth in productivity or output per capita to the firm size distribution concur in advancing the entrepreneurial nature of small firms as one of the potential drivers (Beck et al., 2005; Robbins et al., 2000). As such, they are complemented theoretically by a larger body of research relating other, more 'direct' measures of entrepreneurship – rates of entry, exit, net entry, self-employment and business ownership – to measures of regional or national economic performance.

The association between the firm size distribution and productivity is orchestrated by a range of mechanisms. Carree et al. (2002) classify them as enhancing 'static' or 'dynamic' efficiency. The former is the result of factors pushing existing technology endowments closer towards the optimal allocation, the latter implies the development of new technology to address equivalent or new business opportunities. One can expect static efficiency to be affected by the levels of competition, flexibility and scale economies that characterize an economy. Its organizational texture and the resulting implications in terms of incentives can play a role as well. Ceteris paribus, an increase in the relative footprint of small firms, e.g. in terms of employment, is likely to imply that more firms are active in the economy. The presence of more firms can be expected to augment competition in the product market. More competition has been shown to increase the efficiency at which existing resources are being used. Nickell (1996), Nickell et al. (1997) and Lever and Nieuwenhuijsen (1999) provide evidence that an increased number of competitors boosts total factor productivity (Carree & Thurik, 2002). A relative lack of flexibility as opposed to their small counterparts makes large firms less suited to cope with the increased volatility of current day markets (cf. supra). Their more rigid nature is among other factors fed by the larger regulatory burdens they have to comply with. They are for instance more likely to be unionized, which increases the odds that a part of their labour force is left idle in times of lower demand. The latter exerts a downward pressure on firm level labour productivity (Acs & Audretsch, 1989). In the form of forgone scale economies, Carree and Thurik (2008) and Braunerhjelm and Borgman (2004) attribute potential negative productivity-effects to larger shares of smallness. Technological progress may have lowered size thresholds at which firms can reach maximal efficiency but it has not abolished them. Van Stel et al. (2005) point, albeit indirectly, to the more straightforward incentive structure of small firms to explain the productivity enhancing effect of more smallness. Self-employed business owners – and thus small businesses – may be inclined to work longer hours and more efficiently as their income is strongly linked to their working effort.

Further productivity-effects of an increasing allocation of resources towards small businesses emerge from the suitability of the latter as vehicle for entrepreneurship. When surfacing in the form of imitative entry, entrepreneurship affects the degree of competition in the sense referred to above: increasing what Carree and Thurik (2002) identify as 'static efficiency' by optimally exploiting existing production techniques. The three mechanisms Audretsch and Keilbach (2004) underline to motivate the productivity-enhancing capability of entrepreneurship, depart from a more narrow definition of it in which its role in the process of change is emphasised. These mechanisms described in the next 2 paragraphs are expected to fuel increases in what Carree and Thurik (2002) refer to as 'dynamic efficiency'.

Audretsch and Keilbach (2004) equally embrace the idea that the expansion of the firm population fuelled by new entry is beneficial for the degree of competition in the economy. Hereby however they refer to the competition between entrepreneurs for new ideas rather than the product market competition improving static efficiency. Furman et al. (2002) suggest that the rivalry among local ventures to develop an idea into the best possible commercial application has a beneficial effect on a country's capacity to innovate. Audretsch and Keilbach (2004) furthermore emphasize the emergence of opportunities in other parts of the value chain when more firms become active in the same niche: the demand for complementary inputs and services can increase to a point where it becomes interesting enough for other small niche firms to specialize in it. Next, Audretsch and Keilbach (2004) advance the diversity-increasing potential of entrepreneurship. When one assumes that each new organization represents a unique approach, more entrepreneurship not only increases the number of enterprises, but also the variety of enterprises in a location. A larger variety of approaches, resulting from distinctive mixes of knowledge pieces, positively affects the odds that a winner will emerge from the selection process of which entrepreneurship is the engine (Jovanovic, 1982; Audretsch & Keilbach, 2004; Bosma et al., 2011). The performance-increasing effect of diversity is based on the existence of Jacobian externalities (Jacobs, 1969): economically-relevant knowledge is more likely the result from the exchange of knowledge across economic agents with diverse but complementary knowledge bases than from peers sharing the same knowledge base (Audretsch & Keilbach, 2004).

The core mechanism by which entrepreneurship contributes to dynamic efficiency and thus long-term economic growth forms the starting point for most theoretical contributions emphasising the capacity of entrepreneurship to induce creative destruction.[2] Both of the abovementioned rationales according to which entrepreneurship is expected to enhance dynamic efficiency – by spurring competition over the same ideas and inducing variety

[2] To our knowledge.

through the pursuit of different mixes of knowledge pieces – depart from the same perspective on the role of entrepreneurship, i.e. a knowledge transmission mechanism. A body of theoretical and empirical research (e.g. Audretsch et al., 2008; Baumol, 2004; Audretsch & Keilbach, 2004; Braunerhjelm et al., 2010; Acs et al., 1994; see Braunerhjelm, 2007 for an overview) has been devoted in the past decades to this aspect of the economics of knowledge that initially was left underexposed by pioneers of endogenous growth theory like Romer (1986; 1990), Aghion and Howitt (1992) and Lucas (1988) (Wennekers & Thurik, 1999). Audretsch and Keilbach (2004) refer to this function of entrepreneurship as the 2nd of 2 major channels along which knowledge can spill over.[3] Inherent uncertainty regarding the economic value of new knowledge created by public and private R&D, with large incumbent firms accounting for the bulk of the latter, withholds R&D investors purposely or unknowingly from fully exploiting it. Unknowingly because of knowledge asymmetries between scientists, engineers or knowledge workers active in an incumbent firm and the decision-making bureaucracy. When the former place greater value on their ideas than the latter, they might choose to appropriate the value of their new knowledge in a start-up or a small firm less biased by these asymmetries (Audretsch & Keilbach, 2004). Purposely because of the uncertain outcomes of and thus the risky investment involved with transforming new knowledge into new products and processes. According to Audretsch et al. (2008) incumbents will only engage in knowledge capital investments to the extent these risks remain calculable. At a certain point the uncertainty surrounding an idea becomes too large for an incumbent and it will take the commitment and focus of 1 or more entrepreneurs recognizing the opportunity and willing to 'bet' on it to achieve actual innovation. Baumol (2004) attributes the larger share of breakthrough innovations accounted for by small firms to this dichotomy. He explicitly assigns different but complementary roles to small – entrepreneurial ventures – and large firms – incumbents – in innovation systems. Oligopolistic competition between a relatively limited amount of very large firms, particularly in high-tech industries, forces incumbents to keep innovating but in a very risk-free and path-dependent way. Interests in existing products and markets biases their assessment of new ideas, especially when they bear the capacity to disrupt their current business model. Routinized innovation management processes are implemented in order to address this competition in a seemingly manageable way. The result is an ever-increasing stream of incremental improvements to existing products and processes, multiplying capacity and speed and increasing reliability and user-friendliness originating from incumbents. Whether they spilled over from larger organizations or not, the development of more experimental ideas encompassing an abundance of unknown parameters is more likely to be left to the judgment and guts of 1 or multiple entrepreneurial ventures. The selection process driven by the market mechanism allocating finance and product market share eventually determines which of these ventures translate in commercial success stories (cf. Jovanovic, 1982). The ideas preceding radical innovations tend to comply with this description and are therefore more likely to last in the pipeline of the small business economy.

Empirical literature review

A number of studies using countries as the unit of analysis have empirically addressed the relation between productivity or output per capita and the distribution of employment across firms of different sizes. For a set of 45 countries highly varying in terms of economic development, Beck et al (2005) find evidence of a strong, positive association between the importance of SMEs (1990-2000) and, simultaneously, the average growth of GDP per

[3] Cohen and Levinthal (1989) framed the first one by suggesting that performing in-house R&D as a firm not only generates new knowledge, but also increases the firm's 'absorptive capacity': its ability to assimilate and exploit knowledge created externally.

capita.[4] They fail however to confirm this finding confidently for a lagged version of the SME footprint, thus rejecting the hypothesis that SMEs exert a causal impact on growth. For a panel (1986-1995) of 48 contiguous states in the US, Robbins et al. (2000) find proof that the share of employment accounted for by firms staffed with less than 20 FTEs positively correlates with simultaneous growth in labour productivity. They fail to confirm these results for the share accounted for by firms employing less than 500 FTEs.

A larger amount of comparable studies have relied on more focussed measures of entrepreneurship. Within the spectrum of proxies relied upon in prior research, the creation of new ventures presents itself as the most straightforward expression of entrepreneurship. A range of within-country studies have examined the association between firm births and productivity at the regional level. Audretsch and Keilbach, (2004) assess for a cross-section of 327 West German Kreise the degree to which cross-regional start-up rates can help to explain variation in the gross regional product. Controlling for the amount of labour inputs in the framework of a production function, they confirmed that entrepreneurship capital is a key factor in explaining differences in regional output. For a more recent sample of German regions, Audretsch et al. (2008) prove that the start-up rate in a number of high-tech manufacturing sectors and IT positively affects subsequent manufacturing productivity. For a set of Spanish regions, Callejon and Segarra (1999) identify a productivity-enhancing effect of increased rates of entry and exit in the manufacturing sector. Bosma et al. (2011) obtain comparable results for the Dutch service sector but fail to do so for the manufacturing sector.[5]

Data issues have refrained scholars from assessing the validity of equivalent research questions at the national level. Gaps in the availability of data on new firm formation or a lack of consistency in the measures provided by countries that did keep track of it lie at the origin of this vacuum. In an attempt to address this lacuna, at the end of the 90s the Global Entrepreneurship Monitor (GEM) was set up by a number of entrepreneurship scholars, ordering the assembly of firm entry indicators across 37 developed and emerging countries in a consistent manner. The sustained efforts of GEM participants resulting in a multi-year dataset of harmonized firm entry measures have greatly facilitated cross-country analysis of the impact of new firm formation on national economic performance. Among the empirical studies exploiting this novel source of data, Wong et al. (2005) are (and remain) the first to have addressed the productivity implications of new business creation.[6] An augmented Cobb-Douglas production function is used to explore firm formation and technological innovation as separate determinants of growth. Only the creation of businesses with high potential – implying compliance with 4 criteria regarding expected growth, expected market coverage/impact and novelty of the used technology – is found to have a positive impact on simultaneous productivity growth. None of the other GEM indicators, new business creation overall – irrespective of such criteria –, businesses creation out of opportunity or out of necessity, can be positively associated with productivity growth.

Finally, another often casted candidate to proxy entrepreneurial behaviour has been the number of self-employed. To a certain extent this construct suffers from comparable flaws as the rate of small business employment when it comes to proxying the degree of

[4] SME threshold: < 250 FTEs

[5] Comparable studies departing from the region as unit of analysis have focussed on the association between new firm formation rates and output, e. g. Dejardin (2011), or employment, e. g. Van Stel and Suddle (2008), Van Stel and Storey (2004), Fritsch and Mueller (2007) and Acs and Armington (2004).

[6] Van Stel et al. (2005) and Hessels and Van Stel (2011) assess the relation between new firm formation and GDP growth.

entrepreneurship. As opposed to the formation of new businesses it has the advantage of being available across countries on a more widespread basis in time. Effects on productivity or per capita output are empirically analysed in Carree et al. (2002), Carree and Thurik (2008) and Braunerhjelm and Borgman (2004).[7] For a panel of 23 OECD countries, Carree et al. (2002) find that deviations between the actual and equilibrium share of business owners in the labour force have a negative effect on GDP per capita growth in the next 4 years. Using the same dataset, Carree and Thurik (2008) devote particular attention to the lag structure of the effects of changes in the number of businesses but fail to observe a significant effect on productivity over any of the included lags. Braunerhjelm and Borgman (2004) model productivity in a range of industries in 70 Swedish regions using self-employment amongst a selection of other predictors. Whereas a clear positive effect can be witnessed for the service sector, results are less conclusive for manufacturing.

Research hypotheses

In the empirical part of this paper we aim to contribute to the abovementioned literature investigating the productivity implications for a country of increasingly becoming a small business economy. The first research hypothesis closely adheres to the abovementioned prior research by investigating the effects of industrial restructuring on growth, with industrial structure proxied for by the firm size distribution of employment (Beck et al., 2005; Robbins et al., 2000; Carree, 2002; Carree & Thurik, 1998; Audretsch et al., 2002). The second research hypothesis exploits the availability of new data proxying the firm size and age distribution of knowledge capital.

Hypothesis 1: an increasing footprint of small businesses in the industrial structure of a country has a positive impact on subsequent national productivity.

Hypothesis 2: an increasing footprint of small businesses in *a country's knowledge capital* has a positive impact on subsequent national productivity.

The footprint of small businesses in the industrial structure is proxied by the firm size distribution of employment. By relying on the small business stake in employment we aim to assess the impact of its prevalence in the 'overall' economy as opposed to the 'knowledge' economy (cf. infra). We assume it to pick up the effects of more activity accounted for by the 'average' small firm rather than the small firm operating at the frontier of new knowledge. Especially when compared with labour productivity in the short run, we expect the 'broad' economy measure to be well suited to pick up the effects of more smallness on static efficiency (cf. supra).

The 2nd research hypothesis zooms in on the subpopulation of firms that contribute to renewing the national stock of knowledge capital by deploying inventive activities. An increased share of smallness in the knowledge economy can be expected to increase dynamic efficiency. Theoretically this hypothesis mainly builds on Baumol's (2004) allocation of different roles towards large and small firms in the innovation process with the latter being more likely to introduce breakthrough innovation (cf. supra). To the extent a linear relation exists between the quantity of small firm inventions and the odds that an actual quality innovation emerges from that pool of inventions, one can assume that a larger share of

[7] Again, comparable studies departing from the region as unit of analysis have focussed on the association between self-employment rates and output, e. g. Braunerhjelm et al. (2010), Blanchflower (2000) and Carree and Thurik (2008), or employment, e. g. Blanchflower (2000), Audretsch & Thurik (1998; 2000), Carree and Thurik (2008).

smallness in national inventive activities and thus in the resulting stock of knowledge capital positively affects productivity. Assuming that more smallness is often a reflection of the presence of more firms, a larger share of innovative activity accounted for by small firms should also boost productivity in fiercening the competition for ideas and increasing the variety of approaches by which these ideas are developed (cf. supra).

Methodology

We use the neo-classical growth model (Nadiri, 1993; Audretsch & Keilbach, 2004; Wong et al., 2005) which is based on an augmented Cobb-Douglas production function:

$$Y = A^O K^{\propto} L^{\beta}$$

Where Y = output, A^O= disembodied factor productivity, K = stock of physical capital and L = labour employed. Assuming constant returns to scale, $\alpha + \beta = 1$, both sides of the equation are then divided by labour. Taking natural logs results in the following model to estimate labour productivity:

$$\ln\left(\frac{Y}{L}\right) = lnA^o + \propto ln\left(\frac{K}{L}\right)$$

Following the approach by Wong et al. (2005), we assume that disembodied factor productivity A^O is determined by the normalized stock of knowledge capital and 3 focal measures capturing the footprint of (young) small businesses in the stock of knowledge capital and the overall industrial structure. The knowledge capital based constructs are derived from patent data. Due to their codified nature, patents yield a paper trail of inventive activity, providing detailed information among others regarding its inventors, applicants, their institutional affiliations and geographic origins. Patent counts have traditionally been used as a measure of innovative output. Obviously, not every innovation gets patented, but at an aggregate level, in our case the country level and over time, it is deemed to have informative value as a proxy for the evolution of overall inventive activity (Porter & Stern, 2000; Furman et al., 2002; Ulku, 2004). The stock of knowledge capital (KNOWL_CAP_ST) is measured departing from annual, per-country patent counts. Patents from all sectors – the small business sector, the incumbent sector, universities, individuals, government and non-profit institutions etc. – are incorporated in this indicator to capture the full breadth of national inventive capacity in the model. Yearly stock values were obtained by aggregating counts from the current and previous application years. More specifically, patent counts for the current year were added to the stock value from the previous year, depreciated at a rate of 20%. After all, in line with prior research one can assume that a share of the effects of investment in innovation transcend the short run.[8] The stock of knowledge capital was normalized by employment (per 1000 FTEs) to capture its intensity and to avoid overweighing the impact of a number of large countries in the obtained coefficient estimates (cf. Audretsch et al., 2008; Ulku, 2004).

[8] All patent statistics were extracted from EPO's Worldwide Patent Statistical Database 'PATSTAT' (Autumn version 2014). Depreciation of the patent stock at a rate of 20% per year is based on the perpetual inventory method described in Ulku (2004; 2007). The patent stock variable incorporates annual EPO patent counts from 1970 onwards. The restriction of our attention to EPO patents can be easily justified given the geographical reach of our dataset and their costliness which among other factors is a consequence of their supra-national character. Counts of them at the macro-level bear the potential to be good signals of R&D input and output levels per country over time.

As suggested in the previous section, the general stock of knowledge capital measure is complemented by 2 indicators measuring the degree of small firm engagement in innovative activity and an equivalent employment-based indicator controlling for overall small firm activity. Apart from providing a test for the validity of research hypothesis 1, incorporation of the latter indicator should assure that increased innovative activity of small firms is not simply capturing the potential productivity effects of an increase in small business activity in general.

Determining the degree to which national innovation systems have been fuelled by small business , is based on the assignment of patents to small and large firms. For the large majority of European countries we had access to such data. The methodology that was adopted to allocate patents to European firm data on a large scale is presented in Eurostat (2014).[9] Due to shortcomings in the matching methodology and data gaps in the financial database – among others the result of country-specific disclosure exemptions rewarded to certain company types – only for approximately 84% of the corporate applicants in Europe, firm size could be determined (see Table 1 for per-country matching rates). We assume however that these country-level constraints equally hold for all years of the sample and as such are captured by estimating coefficients using empirical techniques that account for country fixed effects (cf. infra). Equivalently we expect the fixed effect components of the model proposed below to absorb country differences in industrial composition and their underlying propensity to patent (Porter & Stern 2000). Whereas applicant address information was used to match corporate patents to firms in the financial database, in line with previous research efforts (e.g. Ulku, 2004; Ulku, 2007; Wong et al., 2005) the mapping of innovative activity was based on inventor address information. Finally, the footprint of small businesses in the stock of knowledge capital (%_SMALL_in_KNOWL_CAP) was measured by computing the share of small firms in the stock of patents assigned to firms with identified size. Conform the computation stock of knowledge capital variable, underlying small firm and large firm patent stocks were expected to depreciate at an annual rate of 20%.[10]

_ Insert Table 1 here _

Note that the effects of small and large firm engagement in innovative activity could not just be measured separately by plugging their respective patent stocks normalized by the amount of people they employ into the equation: underlying factors, e.g. knowledge spill-overs, appear to evoke high rates of correlation amongst both constructs – more than 0.92 even when using mean-centered versions to account for country effects – and with the stocks of knowledge capital registered for by the national innovation system as a whole. Coefficient estimates resulting from testing such a model would be biased by multicollinearity. In

[9] The lack of dynamic shareholder data in BvD's Amadeus (a database gathering annual account information) withheld us from determining firm size at the business group level for the allocation used in this paper. In contrast with the matching exercise presented in Eurostat (2014), firm size was determined dynamically by linking patents to financial information from the financial years that corresponded with the patent application filing year. In addition financial account data from Amadeus 2012 was enriched with equivalent information from earlier versions (2004 and 2007) to dispose of financial information in the earliest years of the matched sample (1999-2011) and to account for the BvD rule to discard companies not filing accounts for 5 years in a row. The firm size – or rather entity size – classification for patenting companies from 1999 onwards was based on the European Commission SME definition (2005): enterprises that employ fewer than 250 employees and which have an annual turnover not exceeding 50 million euro, and/or an annual balance sheet total not exceeding 43 million euro.

[10] Whereas annual counts of corporate patents were available before 1999, mappings of them to small and large firms were not. The computation of backward looking patent stocks per firm size was therefore based on the assumption that the 1999 firm size distribution of patents also applied to pre-1999 annual corporate patent counts.

addition, retaining the undivided stock of knowledge capital for these economies as a whole as variable in the core model enhances comparability with prior tests of endogenous growth models. The within variance of the share value that is used instead captures to what extent small firms have shown relative over- or underactivity in R&D in comparison with their large counterparts. Hereby we maintain the reasonable assumption that small and large firm innovative activities do not have an opposite effect on economic productivity which would hamper interpretation of coefficient estimates for %_SMALL_in_KNOWL_CAP. At most, one of them can have a relatively larger impact on productivity which would be supported empirically by proving that the overactivity of that side across time significantly correlates with dynamic changes in labour productivity. In line with research hypothesis 2a elaborated above we expect that to be the small innovators.

Given that the large majority of patents in Europe can be assigned to the manufacturing industry (Fraunhofer, 2003), downloads of observations for the non-patent based variables of country c in year t were restricted to that sector.[11] Indicators for value added at factor cost (VAFC), the number of persons employees (EMPL), the stock of investment in physical capital (PHYS_CAP_ST) and the share of small firms in corporate employment (%_SMALL_in_EMPL) were extracted from Eurostat.[12] [13] Furthermore, time dummies representing each year of observation are included to control for Europe-wide business-cycle effects. The limited number of observations does not allow for many competing explanatory

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[11] Note that a more fine-grained investigation per subsector (2-digit NACE class) in the manufacturing industry was not feasible. In the first place subindustry-level numbers were more fragmented than the data for the manufacturing industry as a whole. An update of the NACE classification scheme in the course of the 2000s equally withheld us from digging deeper. The lack of correspondence between a share of the old and new NACE classes and the absence of an update of historical data conform the new scheme obstructed subindustry analysis as presented for instance in Ulku (2007). Comparison of overlapping NACE rev. 1.1 and NACE rev. 2 observations for the manufacturing industry as a whole (available for the years 2005-2007) suggested that both schemes were consistent enough at the industry-level to extend the NACE rev. 1.1 time series available up to 2007 with NACE rev. 2 observations until 2010. Note that nevertheless a correction was applied to the latter observations using factors computed by comparing 2005-2007 observations that were available for both NACE schemes. Sensitivity analysis confirmed the robustness of the regression results to the use of the minimum, maximum and average values obtained for these factors.

[12] The resulting set of 23 countries consists of: Austria, Belgium, Germany, Denmark, Finland, France, United Kingdom, the Netherlands, Norway, Slovenia, Sweden (INNOVATION LEADERS), Bulgaria, Czech Republic, Estonia, Greece, Hungary, Italy, Latvia, Poland, Portugal, Romania, Slovakia and Spain (INNOVATION FOLLOWERS). Other European countries were discarded for multiple reasons: a lack of employment, investment or gross added value statistics available to the public or a too low rate of patenting companies matched to companies in the financial database, as such hampering a representative image of the distribution of patents between incumbents and small businesses. Following the example of Carree and Thurik (2008), 2 countries, in our case Ireland and Luxemburg, were discarded from the sample due to the nature of their economies. We assume the variation in productivity over time for these countries to have been affected too much by fiscal optimization strategies of multinationals involving local subsidiaries rather than being evoked by entrepreneurship and technological innovation dynamics. For other countries maintaining multinational-friendly tax schemes (e.g. Belgium, the Netherlands) we expect the effect of these latter, more structural determinants of economic performance to remain dominant. 3 observations for the United Kingdom (2008-2010) were removed based on outlying labour productivity values.

[13] All currency-based series – expressed in Euro – were deflated using per country GDP price deflators (World Bank WDI website). A stock variant of the investment in physical capital was not directly available on the Eurostat website or on any publicly available, related source of data. To account for this deficiency we computed one ourselves departing from the yearly observations of ‘gross investment in tangible goods’ provided on the Eurostat website to which we applied a yearly depreciation rate of 5.8%. Available only from 1995 onwards, we assumed that gross investment in tangible goods grew at an annual rate of 4.5% beforehand. Both rates were taken from Bosma et al. (2011). Finally remark that the allocation of employment to large and small firms was based exclusively on the staff count criterion (250 FTEs) as the Eurostat website only reports the distributions of employment accordingly.

variables, therefore we refrain from adding additional controls listed in studies such as Sala-I-Martin (1997). We assume that the fixed effects approach we adopt in the analysis absorbs cross-country variance determined by structural determinants of economic performance that change more gradually over time (Van Stel et al., 2005).[14] Conform previous research all knowledge capital related indicators are lagged since it is assumed that it takes a while for the first effects of innovative activity on economic performance to surface. Given the limited time-window at our disposition in which patents were mapped according to firm size, we opted for a relatively short 1-year time lag. Expressing independent variables in lags also helps safeguarding results from the potential bias caused by endogeneity. Accordingly, the small business employment variable capturing the 'broad' economy implications of more smallness and the stock of physical capital normalized by labour were also lagged by 1 year.

The resulting equation to be estimated using panel data techniques is:

$$\log\left(\frac{\text{VAFC}}{\text{EMPL}}\right)_{c,t} = \propto + \beta_1.\log\left(\frac{\text{PHYS CAP ST}}{\text{EMPL}}\right)_{c,t\text{-}1} + \beta_3.\left(\frac{\text{KNOWL CAP ST}}{\text{EMPL}}\right)_{c,t\text{-}1}$$

$$+\beta_4.\%\ \text{SMALL in EMPL}_{c,t\text{-}1} + \beta_5.\%\ \text{SMALL in KNOWL CAP}_{c,t\text{-}1} + \beta_6.\%\ \text{YOUNG in SMALL KNOWL CAP}_{c,t\text{-}1}$$

$$+\beta_7.\text{dummy(year=2001)} + \ldots + \beta_{15}.\text{dummy(year=2010)} + u_c + \varepsilon_{ct}$$

Results

The panel dataset finally subjected to empirical analysis comprised 11 years of post-millennial observations (2000-2010) for 23 European countries. To shed some light on the evolution of the economic texture over time,

Table 2 reports per country observations for the main variables at the beginning and the end of the investigated time window. Countries are presented consecutively according to their rank in the Innovation Union Scoreboard (IUS) (2015). Small business participation shares in employment suggest that the shift towards smallness in the Europe witnessed from the 70s onwards has not ceased in the 2000s: for 19 out of the 23 countries its stake continues to increase. Absolute employment numbers for the manufacturing industry confirm that the manufacturing industry is in decline in Europe, although comparison with 2007 observations suggests that trend to be amplified by the financial crisis that struck Europe from the second half of 2008 onwards. Not surprisingly, large differences can be observed between patent stock per employee rates at the head and in the tail of the IUS ranking. Given the changing role of small firms in economies becoming more knowledge-intensive (cf. supra), the remainder of the empirical analysis will be repeated for the full set of countries and 2 non-overlapping subsets of national economies leading and following in terms of innovation according to the IUS.[15]

_Insert Table 2 here _

The pairwise correlations between the variables comprising the model are presented in Table 3. Taking a look at bivariate associations between the prevalence of smallness and labour productivity across the 3 sets of data suggests that different dynamics are at play in the core of Europe and in more peripheral member states.

[14] E.g. schooling, climate, institutional quality and quality of property rights etc.

[15] The split data approach is also adopted in Van Stel et al. (2005) and Hessels and Van Stel (2011).

_ Insert Table 3 here _

Table 4 reports estimates, including robust standard errors, for a dynamic variant of the model. This implies that a lagged version of the dependent variable is included among the predictors. We expect it to pick up the effects of non-modelled factors causing shifts in productivity spreading out over multiple years (Frietsch et al., 2014). The reported estimators were obtained using the GMM methodology introduced by Arellano and Bond (1991).[16] For dynamic panel data models, the according estimates can be deemed to be less biased than the ones one would obtain applying OLS. In addition, this econometric technique maximizes consistence by incorporating lagged endogenous variables as their own instruments (Roodman, 2009). The latter is of concern here since patent applications cannot be expected to be strictly exogenous when equated against labour productivity. The unobserved heterogeneity that further remains at the country-level is expected to be accounted for by the first difference transformation of the variables.

_ insert Table 4 here _

The results reported in Table 4 confirm the validity of research hypothesis 1 for the full set of countries. Split dataset results suggest that this pattern is mainly supported by the economies that lag relatively more behind in terms of innovation according to the European Commission (2015). To the extent that effects of the mechanisms enhancing dynamic efficiency are captured by %_SMALL_in_KNOWL_CAP and given the 1-year lag, one could expect the positive effect to be mainly fed by the static efficiency gains attached to more smallness. Research hypothesis 2 is only validated for the leading innovator countries. Only in the mature European knowledge economies dynamic efficiency gains appear to be attached to upsurges in the share of knowledge capital accounted for by small firms. Given that large innovators on average account for larger average contributions to the stock of knowledge capital in these leading countries, this finding supports the innovation eco-system view described by Baumol (2004) and Audretsch et al. (2008) with separate but complementary roles for small and large firms. Knowledge spill-overs from the latter provide a constant supply of entrepreneurial opportunities that can be expected to be less intense in the follower countries.

The main caveat to the abovementioned interpretation of the coefficients obtained for %_SMALL_in_KNOWL_CAP is the potential contingent effect of firm size on the extent to which a firm’s engagement in innovative activities is reflected by patent counts. A number of mechanisms favour the reliance of small firms on IP rights to protect their innovations. SMEs have a greater need for strategic alliances in production and marketing. Therefore more of their transactions occur through the external market rather than within the firm. Lower levels of trust between transacting parties make legal contracts more attractive (Jensen & Webster, 2006). Moreover, SMEs face information asymmetries various markets they come in touch with. Patents can be used as signal for the quality of the firm to rebalance the distribution of information with potential investors and customers (Blind et al., 2006). Other rationales favour a larger propensity of large firms to seek patent protection: they are less financially constrained, maintain in-house IP departments with experience in the patenting process and are more capable to enforce their patents when facing litigation (Holgersson 2006; Blind et al., 2006). The latter mechanisms have been perceived as and proven to be dominant in prior

[16] The ‘xtabond2’ procedure.was used to conduct this analysis in Stata (Roodman, 2009).

research (Blind et al., 2006; De Rassenfosse, 2012). To the extent that strategic patenting behaviour by large firms blurs the correlation between changes in their patent stock over time and their engagement towards innovation, the positive coefficient reported for %_SMALL_in_KNOWL_CAP might simply reflect the larger suitability of small firm patent portfolios to proxy evolutions in national innovative activity over time. Another caveat is mainly of concern for the follower country findings: the relatively low patent volumes that are used to proxy characteristics of their knowledge capital endowments bear the capacity to introduce measurement error (Dejardin, 2011).

Extension

An obvious extension of research hypothesis 2 is the question whether it is the young, the mature or both types of small firms that have an edge over large firms in taking up the agent of change role. One might expect the 1st scenario to be the case as one could interpret Baumol's (2004) role description of small innovators to be mainly embodied by start-ups. Not coincidently, the more recent body of research linking entrepreneurship to growth has favored the use of start-ups as unit of analysis over firm size distribution indicators that fail to distinguish seasoned family firms and large firm subsidiaries from actual entrepreneurial ventures.

The indicators included to explore this proposition, %_YOUNG_SMALL _in _KNOWL_CAP and %_MATURE_SMALL _in _KNOWL_CAP, were calculated conform the approach that was adopted to obtain %_SMALL_in_KNOWL_CAP. Accordingly, they represent the share of young and mature small firms in the stock of patents assigned to companies with identified size. The stock of patents filed by small firms before or during the 10th year of their incorporation comprise the denominator of the former, the stock of remaining small firm patents the equivalent of the latter. Results for models disambiguating the footprint of small innovators as described here are presented in Table 5.

_ Insert Table 5 here _

Highly significant evidence is provided that in the leading countries small innovator impact is endorsed by the initiative of young firms. This finding fits the pattern predicted by the knowledge spill-over theory of entrepreneurship (Acs et al., 2013): knowledge-intensive start-up activity with impact does not happen in isolation, it is contingent on the presence of critical knowledge capital mass in the leader countries. The latter is embodied by clusters of large, established R&D investors fuelling streams of knowledge spill-overs perceived by start-ups as business opportunities. More striking is the consistent observation for each sample of countries, albeit less significant for the leading countries, that mature small innovator activity also significantly matters. Delineating one or more rationales explaining this observation is more challenging. As explained above, their smallness by itself spurs entrepreneurial initiative as organizational structures tend to be less complex and incentives for owner-managers more straightforward. To explain why this pattern recurs in all country subsets we look in the direction of the core of established SMEs, traditionally referred to as the Mittelstand in German speaking countries. Often serving in niche industries in which more mature technologies prevail they might be less dependent on spill-overs from large incumbents than edge technology start-ups. The evidence could therefore suggest that they seem to be capable of rejuvenating themselves sufficiently to persist at the frontier of knowledge in their field. If that would effectively hold, their appraisal by policymakers as backbone of the European economy might also be justified from the perspective of technological change.

Concluding remarks

Previous research has suggested that the prevalence of small firms in Europe has been on the rise since the 1970s (Wennekers & Thurik, 1999). Post-millennial observations of the employment share accounted for by small business confirms that this evolution has not ceased to stop. In the current paper an attempt has been provided to explain the implications of more smallness for the productivity of these economies, both theoretically as well as empirically. In doing so we aim at contributing to a recent route of inquiry in growth accounting research explaining the residual remaining in endogenous growth theory by referring to entrepreneurship capital. Thriving as vehicle of entrepreneurship, small firm activity in general has been a frequently casted candidate proxying entrepreneurship in prior empirical contributions. In explaining productivity however, effects associated with the prevalence of smallness are not only driven by entrepreneurship. A classification was presented dividing underlying mechanisms associating smallness with national labour productivity in 2 categories: a first one affecting the static efficiency and a second one the dynamic efficiency of an economy. Static efficiency gains result from product market competition, increased flexibility and the more straightforward incentive structure associated with more smallness. Foregone scale economies in contrast deteriorate it. Dynamic efficiency is fuelled by the effects of more smallness on the pool of ideas available within a knowledge economy: more smallness is associated with tougher competition over their development, more diverse approaches to do so and higher odds that an effective breakthrough emerges from the selection process.

The empirical analysis presented in this paper exploits the availability of firm size distribution information for annual employment and corporate patenting statistics to estimate the efficiency-increasing effects of more smallness. In the discussion of the obtained results, an interpretation is advanced associating increases in the latter with dynamic and increases in the former with static efficiency gains. Findings reveal that the prevalence of smallness in employment positively correlates with productivity in the manufacturing sector in Europe as a whole. No additional effects appear to stem from small firm footprint changes in the stock of knowledge capital that is proxied using patent statistics. This aggregate pattern however disguises differential dynamics unfolding in different parts of Europe. Results obtained for countries with large knowledge capital endowments ('innovation leaders') signal a clear positive relationship between productivity and the footprint of SMEs in the stock of knowledge capital whereas such a positive relationship is not to be observed for less knowledge-intensive economies ('innovation followers'). Neither do we observe productivity implications of employment distribution changes in the more knowledge-intensive subset of countries. A young-mature firm disambiguation of the small firm footprint in knowledge capital revealed the consistent impact of mature small innovators across all country samples. The young small firm contribution only mattered in innovation leading countries. In sum, findings do not contradict Baumol's (2004) assignment of different roles to (young) small and large firms in innovation systems with the former being more suited to introduce breakthrough innovations. A special role appears to be reserved for mature small mittelstand firms in supporting dynamic efficiency across Europe as a whole. The main caveat that could undermine the validity of our results lies in the potential disjunction between patents counts and innovativeness as firms grow larger.

Future research is necessary to further disentangle the mechanics behind the observed effects. Measurement of knowledge spill-overs could help to provide insights about their nature, origins and the direction in which they are heading. Per industry analysis could reveal to which extent the patterns can be observed consistently for low- and high-tech industries.

Further inquiry is also needed to determine the policy implications of our findings. A comparison with results of an equivalent analysis for the US might be enlightening in this respect.

Appendix

Table 1: applicant and patent matching success rates

Country	# corporate applicants	applicant match rate	# corporate patents	patent match rate
AT	6,847	85.7%	16,640	91.3%
BE	5,437	86.2%	15,112	91.9%
BG	90	66.7%	116	73.3%
CY	61	59.0%	71	59.2%
CZ	790	85.2%	1,218	88.5%
DE	55,182	85.4%	254,120	93.2%
DK	4,637	87.3%	12,642	89.6%
EE	93	86.0%	159	87.4%
ES	5,969	76.8%	11,034	81.4%
FI	3,980	87.7%	16,041	91.2%
FR	21,530	79.9%	84,919	87.4%
GB	20,987	92.9%	54,798	93.6%
GR	365	64.9%	503	70.6%
HU	706	75.2%	1,486	81.1%
IE	1,287	87.0%	2,148	86.6%
IT	21,906	84.2%	45,586	85.8%
LT	28	67.9%	38	52.6%
LU	346	66.8%	772	74.7%
LV	93	77.4%	154	86.4%
MT	53	81.1%	79	86.1%
NL	9,830	86.5%	40,559	93.1%
NO	2,698	85.8%	4,955	88.5%
PL	646	78.6%	1,101	79.8%
PT	439	80.4%	682	83.3%
RO	94	86.2%	146	85.6%
SE	8,593	86.8%	29,180	88.8%
SI	406	71.2%	963	80.6%
SK	251	87.3%	335	91.9%
Total	**185,776**	**84.3%**	**633,923**	**90.5%**

Table 2: summary statistics for the European countries (manufacturing) retained in the final sample

Country	labour productivity (in EUR)		# employees (in FTEs)		% small firms in employment		Patent stock per 1000 employees		% small firms in patent stock		% young small firms in patent stock	
	2000	2009	2000	2009	2000	2009	2000	2009	2000	2009	2000	2009
SE	59,892	62,881	791,764	657,720	47.1%	53.3%	11.36	20.09	35.0%	38.9%	20.1%	19.1%
DK	56,386	74,887	488,000	309,792	53.3%	56.7%	6.94	19.52	41.9%	46.4%	26.6%	29.5%
FI	74,909	56,790	435,780	380,972	46.4%	49.5%	10.81	18.03	25.2%	25.3%	19.0%	16.6%
DE	56,732	54,939	7,551,269	6,877,330	45.0%	46.4%	10.97	16.99	35.5%	36.3%	24.2%	18.7%
NL	71,413	69,335	904,778	749,929	63.8%*	67.2%	12.94	25.09	31.6%	33.2%	14.7%	14.9%
GB	59,413	102,766	4,100,152	2,319,583	54.0%	55.2%	5.15	11.46	49.7%	49.2%	31.1%	30.6%
BE	72,821	74,562	676,973	572,433	54.5%	56.2%	7.40	13.88	27.5%	33.8%	16.7%	19.8%
FR	57,409	53,417	4,026,591	3,385,278	53.5%	55.2%	7.57	13.15	29.2%	27.0%	16.8%	13.1%
AT	61,629	62,822	628,754	619,769	56.0%	54.1%	7.58	13.98	43.2%	45.0%	28.6%	25.9%
SI	19,280*	22,321	257,164*	214,495	59.6%*	59.5%	0.78*	2.53	27.2%	17.5%	20.9%	9.5%
NO	78,056	76,002	283,955	260,931	57.8%	62.3%	5.21	9.21	62.0%	60.5%	51.2%	42.2%
EE	9,248	12,247	119,379	101,826	64.9%	75.3%	0.21	1.25	75.5%	63.1%	69.4%	48.2%
CZ	13,158	17,523	1,377,896	1,228,893	55.3%	59.4%	0.17	0.65	42.2%	48.4%	27.5%	25.1%
IT	48,585	39,177	4,821,489	4,337,681	77.0%	77.0%	3.03	5.23	49.9%	51.1%	20.9%	19.3%
PT	22,869	20,936	937,553	746,304	76.3%	82.1%	0.15	0.70	52.3%	53.6%	21.2%	30.9%
ES	47,178	44,051	2,594,842	2,128,109	73.6%	72.4%	1.03	3.13	54.6%	47.0%	28.2%	23.4%
HU	17,766	22,134	756,003	679,548	46.0%	57.8%	0.54	1.26	28.7%	31.5%	21.3%	15.2%
GR	46,299	38,846	223,393	405,279	60.5%	80.7%	1.05	1.27	64.9%	59.5%	41.6%	32.7%
SK	9,278	16,017	411,256	385,598	39.6%	47.5%	0.17	0.55	78.6%	52.4%	75.1%	34.2%
PL	16,637*	17,811	2,402,050*	2,544,669	55.7%	60.0%	0.10*	0.35	71.9%	57.0%	64.5%	34.1%
LV	8,952	7,553	153,516	113,383	61.4%	77.1%	0.10	0.82	79.6%	44.8%	18.4%	38.3%
BG	3,322*	5,113	615,305*	586,806	59.2%*	69.2%	0.09*	0.19	50.7%	29.4%	50.7%	14.3%
RO	5,180	7,512	1,835,416	1,220,984	36.8%	57.3%	0.02	0.12	93.7%	54.2%	93.7%	23.1%

Note: countries are sorted according to their IUS rank / Sources: Eurostat & EPO PATSTAT / *: 2002 value since value for 2000 not available.

Table 3: pairwise correlation analysis

	VAFC / EMPL	PHYS CAP ST / EMPL (1y lag)	KNOWL CAP ST / EMPL (1y lag)	% SMALL in KNOWL CAP (1y lag)	% YOUNG SMALL in KNOWL CAP (1y lag)	% MATURE SMALL in KNOWL CAP (1y lag)
ALL (N = 230)						
PHYS CAP ST / EMPL (1y lag)	0.894***					
KNOWL CAP ST / EMPL (1y lag)	0.761***	0.661***				
% SMALL in KNOWL CAP (1y lag)	-0.306***	-0.306***	-0.454***			
% YOUNG SMALL in KNOWL CAP (1y lag)	-0.396***	-0.347***	-0.426***	0.862***		
% MATURE SMALL in KNOWL CAP (1y lag)	0.203***	0.118*	-0.041	0.362***	-0.156**	
%_SMALL_in_EMPL (1y lag)	-0.110	-0.169**	-0.328***	0.305***	0.024	0.515***
LEADERS (N = 112)						
PHYS CAP ST / EMPL (1y lag)	0.752***					
KNOWL CAP ST / EMPL (1y lag)	0.546***	0.191*				
% SMALL in KNOWL CAP (1y lag)	0.458***	0.252**	-0.178*			
% YOUNG SMALL in KNOWL CAP (1y lag)	0.406***	0.297***	-0.311***	0.953***		
% MATURE SMALL in KNOWL CAP (1y lag)	0.457***	0.102	0.263***	0.688***	0.439***	
%_SMALL_in_EMPL (1y lag)	0.172*	0.057	0.088	0.264***	0.201**	0.290***
FOLLOWERS (N = 118)						
PHYS CAP ST / EMPL (1y lag)	0.791***					
KNOWL CAP ST / EMPL (1y lag)	0.684***	0.544***				
% SMALL in KNOWL CAP (1y lag)	0.024	-0.032	-0.076			
% YOUNG SMALL in KNOWL CAP (1y lag)	-0.296**	-0.245**	-0.344***	0.804***		
% MATURE SMALL in KNOWL CAP (1y lag)	0.560***	0.400***	0.455***	0.235**	-0.386***	
%_SMALL_in_EMPL (1y lag)	0.520***	0.317***	0.466***	0.049***	-0.286***	0.532***

Table 4: dynamic panel data estimators obtained using difference GMM (1 step)

	ALL		LEADERS		FOLLOWERS	
VAFC / EMPL (1y lag)	0.57***	0.546***	0.31***	0.353***	0.636***	0.634***
	(11.02)	(9.62)	(3.52)	(4.60)	(11.96)	(10.51)
PHYS CAP ST / EMPL (1y lag)	-0.046	-0.011	0.123***	0.179***	-0.062	-0.051
	(.59)	(.14)	(3.05)	(2.84)	(.80)	(.79)
KNOWL CAP ST / EMPL (1y lag)	-0.006	-0.007	0.017***	0.009***	-0.017	-0.017
	(1.14)	(1.40)	(4.72)	(2.96)	(.74)	(.74)
%_SMALL_in_EMPL (1y lag)	0.754***	0.962***	-0.041	0.23	0.725***	0.819***
	(2.83)	(4.14)	(.10)	(.65)	(2.83)	(3.09)
% SMALL in KNOWL CAP (1y lag)		0.226		0.668**		0.086
		(1.01)		(2.49)		(.51)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
# observations	206	206	101	101	105	105
# groups	23	23	11	11	12	12
p-value of Hansen statistic	1	1	1	1	1	1
p-value of AB test for AR(1)	0.07	0.06	0.02	0.01	0.1	0.09
p-value of AB test for AR(2)	0.49	0.51	0.39	0.28	0.42	0.41

Dependent variable: VAFC / EMPL; t-statistics between parentheses; * p<0.1; ** p<0.05; *** p<0.01

Table 5: dynamic panel data estimators obtained using difference GMM (1 step)

	ALL	LEADERS	FOLLOWERS
VAFC / EMPL (1y lag)	0.459***	0.354***	0.483***
	(7.59)	(4.83)	(6.57)
PHYS CAP ST / EMPL (1y lag)	0.033	0.171***	0.017
	(.51)	(2.79)	(.32)
KNOWL CAP ST / EMPL (1y lag)	-0.004	0.01***	-0.027
	(.88)	(3.05)	(.83)
%_SMALL_in_EMPL (1y lag)	0.774***	0.176	0.706**
	(3.36)	(.47)	(2.31)
% YOUNG SMALL in KNOWL CAP (1y lag)	0.042	0.57***	-0.001
	(.38)	(3.49)	(.01)
% MATURE SMALL in KNOWL CAP (1y lag)	0.5***	1.064*	0.46***
	(3.85)	(1.68)	(4.07)
Year dummies	Yes	Yes	Yes
# observations	206	101	105
# groups	23	11	12
p-value of Hansen statistic	1	1	1
p-value of AB test for AR(1)	0.04	0.01	0.07
p-value of AB test for AR(2)	0.51	0.28	0.39

Dependent variable: VAFC / EMPL; t-statistics between parentheses; * p<0.1; ** p<0.05; *** p<0.01

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